Journal of Corporate Finance Management and Banking System
Vol: 06, No. 01, Jan-June 2026
ISSN: 2799-1059, DOI: 10.55529/jcfmbs.61.102.113

Research Paper

Corporate financial distress and banking sector vulnerability: an integrated risk assessment approach

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Article Info

Article History:
Received: 12 January 2026
Revised: 20 March 2026
Accepted: 28 March 2026
Published: 14 May 2026

Keywords:
Corporate Financial Distress
Banking Sector Vulnerability
Systemic Risk
Early-Warning Models
Machine Learning
Credit Risk

ABSTRACT

The fragility of the banking sector and the financial distress of corporations are closely related but most of the existing literature considers the development of financial distress of firms and bank's solvency problems as two separate issues. In this research, we offer a multi-layer framework of investigating the connections from firm-level financial distress to bank-level vulnerability by multiple measures, including accounting ratios, market-based metrics and loan-exposure concentration ratios. The framework integrates classical distress-prediction approaches, such as discriminant analysis, logistic regression and structural credit-risk theory with the ensemble machine-learning approach to obtain an interpretable systemic early warning signal. The methodology features four steps: (i) firm-level distress probabilities are estimated based on financial and market indicators; (ii) these distress probabilities are aggregated to obtain exposure-weighted vulnerability measures for banks; (iii) individual banks' vulnerability measures are wrought in with solvency and liquidity indicators; and (iv) a gradient-boosting ensemble (GBE) classifier is used to estimate the systemic vulnerability indicator. The efficiency of the approach proposed is illustrated through a simulated but realistic set of data on the financial characteristics of the distressed firms and distressed banks. Moreover, the gradient-boosting model with integrated feature ranking is superior to the other classic models like logistic regression, discriminant analysis, random forest model, and support vector machines in terms of accuracy, precision, and AUC. The framework has recently demonstrated both an increase in the predictive power of the models, as well as making them more interpretable through an understanding of the mechanisms by which firm-level distress spreads to the risk of the banking sector. The proposed architecture provides a scalable framework for systemic risk monitoring, while empowering regulators, financial institutions, and macroprudential authorities to reinforce financial stability and to detect risks in a timely and more reliable manner.

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1. INTRODUCTION

The financial crises of the last 20 years have each shown that when firms become distressed, a banking-sector fragility follows, as the problems of the banking sector increase the likelihood of a subsequent corporate-sector crisis. Although this is well recognized interdependence, the empirical literature has historically been along two parallel lines. The first track is based on accounting and corporate finance research, and concentrates on developing classifiers based on financial-ratios to predict the failure of individual firms. This stream models the existence of a small number of univariate financial ratios that are able to predict failure and non-failure of firms up to five years prior to failure, which led to the identification of liquidity, profitability and leverage ratios as key indicators of distress [1]. Later, this univariate method was expanded into a multivariate discriminant model: the widely used Z-score model of bankruptcy risk [2] where several ratios were combined into a composite indicator of bankruptcy risk. This was then followed by a conditional logit specification that overcame some statistical drawbacks of the linear discriminant specification, and provided estimates of failure probabilities directly [3]. This then led to methodological concerns, especially with respect to sample selection, as it is possible to have a parameter estimate of the distressed firms that is biased in the case of over-sampling distressed firms relative to their actual prevalence [4].

The second strand of the research is banking and monetary economics and focuses on the stability of financial intermediaries. An early conceptual link was established between the two tracks by considering corporate debt as an option to receive a payoff from the firm i.e., a contingent claim and a bank's portfolio of corporate loans as a portfolio of short positions in put options written on the borrowing firms [5]. This structural structure suggests that the distress of a firm is mechanically connected to the distress of the bank via the value and volatility of the borrower assets but has been used mainly in credit-risk pricing for single issuers rather than to assess the vulnerability of the system. At the same time, the liability side fragility of bank balance sheets was codified by revealing that bank balance sheets financed from demand deposits are inherently vulnerable to self-fulfilling runs of any bank even if its underlying assets are sound [6]. Combined, these two literatures suggest that at least two mechanisms lead to vulnerability of the banking sector: the asset-side vulnerability from the financial situation of the corporate borrowers, and the liability-side vulnerability from depositor and market confidence.

Such a combination of two channels has become increasingly important, particularly in the case of banking systems in advanced economies and emerging economies becoming more focused in terms of industry exposure, as well as the increase in corporate leverage due to the prolonged period of low interest rates. Early-warning measures are increasingly being sought that are able to convert signals of distress of the firm to vulnerability at the bank and system levels, and not just macroprudential signals of stress, which can be misleading and fail to capture the potential for concentration risk at the firm level in particular loan categories. Concurrently, machine learning techniques have significantly enhanced the precision of firm-level distress predictions, but this progress has been limited when it comes to the aggregation issue of aggregating firm-level probabilities to obtain a meaningful risk measure at the bank level.

This paper fills this gap by designing an integrated risk-assessment framework where corporate financial distress prediction is directly linked with vulnerability assessment in the banking system. This framework translates accounting-based ratios, distance-to-default measures derived from the market, and textual or macro-economic signals into the score of firm distress, sums up the scores using the weights of the bank's loan portfolio to create some exposure measure, and finally integrates the exposure scores with interbank contagion channels and bank-specific solvency and liquidity measures into a single systemic vulnerability index. The final early-warning signal is created using an ensemble gradient-boosting classifier, with tests to see how well it can perform compared to traditional statistical and machine-learning models.

There are three implications of this study. First, it presents a clear-cut aggregation mechanism: the exposure-weighted distress concentration measure introduced in Section 3, which explicitly maps the probabilities of distress at the firm level to the vulnerability measure at the bank level, with a link between the two levels of credit events and vulnerability – a link that is missing to a large extent in single-layer bank-failure models. Second, it combines both asset-side credit risk and liability-side liquidity and interbank contagion risk into a single estimable feature set that can then be analyzed together and the relative importance of each channel can be evaluated simultaneously. Third, it compares a contemporary ensemble learning method with classical discriminant and logit specifications and applies the same assessment framework to both to provide a model that can be adapted by supervisory authorities and researchers on financial stability to the institutional data they use. A few sentences give an overview of the contents of a future paper, but the remainder of this paper can be organized as follows: The related literature review is conducted in Section 2, which takes a look at literature on corporate distress prediction and vulnerability of banking-sector. The proposed integrated methodology, where data was constructed, Model was developed and evaluation criteria, is mentioned in Section 3. The outcomes are summarized and the implications discussed in Section 4. The paper ends with the Contributions, Limitations and future research Summary (Section 5).

2. RELATED WORK

There has been substantial development in the corporate distress-prediction literature, and in the banking-stability literature, but little has been done to explore the linkage between the two. This section reviews the two strands and specifically identifies the gap which inspires the integrated framework that is presented in Section 3.

The theory of banking stability followed Diamond and Dybvig's framework of the original bank run in the banking-stability literature has further evolved. A "Global-games re-refinement" of the demand-deposit contract model was added, from which a new class of bank run probability, depending directly on the fundamentals instead of using sunspots allowing a multiplicity of equilibria [7] was obtained. The fact that this refinement exists is important to the present study as it would suggest that - in principle - the probability of bank runs could be represented as a continuous function of observable fundamentals, which is the approach used to construct the bank-level vulnerability index proposed later in this paper. On the corporate side, the classical accounting-ratio approach was extended by creating a reduced-form hazard model of financial distress to financial variables, accounting variables and market-based indicators like equity volatility and excess stock returns, which found that the market-based measure of distress risk explains only part of the distress risk indicated by accounting variables [8]. In many ways their approach reflects in the market-based element of the firm-level scoring module that is used in this paper.

A considerable amount of research arose out of the 2007–2008 global financial crisis, documenting the extent to which the transmission of corporate distress to banking-sector fragility occurred. The robustness and characteristics of corporate governance arrangements were analyzed at financial institutions across the globe, with banks having stronger governance structures on the board and higher institutional ownership showing less losses during the crisis, and more risk taking in the years leading up to the crisis, in comparison to less robust financial institutions [9]. In addition to this approach that focuses on the governance aspects, a multi-factor risk model was developed, specifically designed to assess the funding-liquidity risk of banks, incorporating balance-sheet liquidity indicators as well as market-based measures of funding costs, akin to the bank-level vulnerability module proposed in this paper [10].

A second line of research focused on the credit risk and vulnerability spillover effects between neighboring markets is also explored. The ratio-based distress signals are found to be predictive of credit risk and loan performance even in the context of online peer-to-peer lending platforms, thereby supporting the overall validity of the ratios as indicators of credit risk and loan performance for lending in general [11]. It was investigated whether risk contagion was initiated by endogenous liquidity shocks in the United States and Eurozone interbank markets, thus providing empirical evidence that liquidity shocks can be quickly transmitted from one part of the interbank network to other parts of otherwise sound interbank network, which is the motivation to include an explicit interbank contagion channel in the framework developed here [12]. The effect of leverage on the sensitivity of firms/institutions to funding shocks was examined, and the results have implications for firm-level leverage ratio measurement, with implications for the construction of bank-level exposure measures [13].

Recent contributions have also focused on the information and legal mechanism from corporate distress to bank behaviors. Ownership networks were demonstrated to provide material information for banks in pricing loans and making monitoring decisions and thus ownership exposure concentration should capture not only a monetary exposure but also the importance in terms of underlying ownership and relationship networks [14]. The importance of the bankruptcy design on the ultimate outcome of the financially distressed firms via the credit channel was also explored, showing that bankruptcy systems that allow quicker resolution of distress leads to less ultimate loss of a lending bank upon distress [15]. It shows that the translation of firm distress to bank distress is not straightforward; the institutional and legal environment is an important influence which has been qualitatively introduced in Section 5 of the proposed framework limitations.

However, across these strands, there is typically a consistency that studies targeted at the firm-level distress prediction, from [1], [2], [3], [4], [5], [6], [7], [8] produce good discrimination within the sample of failed and flourishing firms, but do not go so far as making a firm-level probability a metric at the bank level of the broader portfolio risk. On the other hand, the bank-level vulnerability studies, such as the liquidity-risk model [10] or the interbank-contagion evidence [12], usually do not model the distribution of underlying borrower-level vulnerability, but rather treat the bank's vulnerability as a reduced form variable, such as its overall non-performing loan ratio. The fact that two banks can have the same aggregate NPL ratio, but very different underlying risk portfolios – one with numerous larger, independent exposures; another with a few larger, correlated exposures - determines the separation. The former relationship is evidenced in the ownership-network studies [14] and the latter in the credit-channel studies [15] cited above, and both show that this distinction matter significantly for realized losses but neither offers a general-purpose procedure for creating such a decomposition. That is exactly the decomposition – relating the probability of distress at the firm level to the concentration of exposure level at the bank level in a transparent and estimable way – that the framework proposed in Section 3 will offer.

Together, this literature provides three key elements that can serve as foundations for the present study: (i) accounting ratios and market-based indicators can be used with reasonable precision to measure the distress level of a given firm; (ii) the vulnerability of a particular bank depends on two factors: credit exposure (on the asset side) and liquidity/funding risk (on the liability side); and (iii) contagion can arise in two ways: from direct exposure to fellow banks (on the asset side) and from common exposure to correlated borrower risk (on the liability side). There is, however, very little research with a formal integration of these 3 building blocks into a single pipeline that can be estimated empirically in a pipeline that creates a bank-level early-warning signal that can be directly linked to firm distress probabilities. This gap is the type of thing the methodology proposed in the next section is creating a way to close.

3. METHODOLOGY

The conceptual chain outlined in Section 2 is implemented step by step in the proposed framework, which is composed of four stages: (i) calculate a distress score for each firm level, (ii) combine this distress score together with the exposure/weight of the firm and aggregate to the bank level, (iii) incorporate bank-specific vulnerability and liquidity indicators, and (iv) train a supervised learning integrated systemic vulnerability classifier. Overall structure of the framework is summarized in Figure 1.

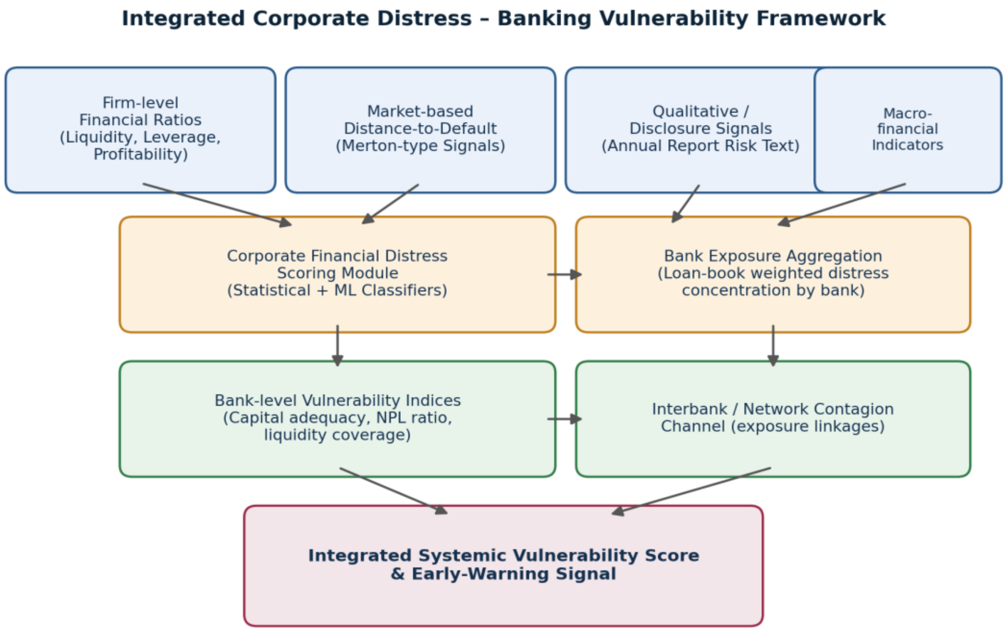

Figure 1. Integrated Corporate Distress Banking Vulnerability Framework, from Firm-Level Inputs Through to the Systemic Vulnerability Signal

The building blocks of the firm-level inputs are of three types, as presented in Figure 1 accounting-based financial ratios, which reflect the firms' liquidity, leverage and profitability metrics, market-based distance-to-default signals following the framework of the structural credit-risk model [5] and macro-financial control variables, which represent the prevailing credit and interest-rate environment. The inputs are given to a corporate financial distress model that generates the corporate financial distress probability score of each firm i at time t, which is known as p(i, t). This module is complemented by two different specifications. The former is a logistic regression equation whose form is $\log [p / (1 - p)] = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + ... + \beta_k X_k$, with X_1 through X_k representing firm-level ratio and market-signal variables. The second (and major) specification is gradient-boosted ensemble of classification trees estimated by using the partial dependence function (PDF) fit using the XGBoost algorithm on the negative gradient of a logistic loss function [16], which fits successively shallow regression trees to the negative gradient of a logistic loss function, and hence is able to recover non-linear interactions among ratios (i.e., leverage and interest coverage) that any linear specification is unable to represent. Table 1 provides a set of illustrative firm-level variables that are used to construct the distress score and mean values of those variables in the constructed set of the distressed firms and non-distressed firms in the constructed dataset used for demonstration in Section 4.

Table 1. Illustrative Firm-Level Financial Ratios: Distressed Vs. Non-Distressed Firms

Financial Ratio Category	**Illustrative Ratio**	**Non-distressed Firms (Mean)**	**Distressed Firms (Mean)**
Financial Ratio Category	Illustrative Ratio	Non-distressed Firms (Mean)	Distressed Firms (Mean)
Liquidity	Current ratio	1.86	0.94
Liquidity	Working capital / Total assets	0.21	-0.06
Leverage	Total debt / Total assets	0.38	0.71
Leverage	Interest coverage ratio	6.42	0.87

Profitability	Return on assets (%)	7.15	-3.92
Profitability	Retained earnings / Total assets	0.24	-0.18
Market-based	Distance-to-default (Merton-type)	3.35	0.79
Efficiency	Sales / Total assets	1.42	0.88

In the illustrative sample, as reported in Table 1, firms facing distress have considerably lower liquidity (current ratio 0.94 against 1.86 for non-distressed firms), significantly higher leverage (0.71 compared to 0.38 for debt-to-assets for distressed and non-distressed firms, respectively) and negative average profitability. The market-based distance-to-default measure also shows significant differences between the two groups, and demonstrates the extra discriminatory information which can come from the market beyond the accounting information [8].

The second step of the framework adds up the probabilities of distress experienced by each firm into a bank-level exposure measure. The exposure-weighted distress concentration for a bank b is calculated as: $EDC(b, t) = \sum_a w(a,b, t)p(a, t)$, where a is a borrowing firm in bank b's loan portfolio at time t and the sum is over all borrowers in bank b's loan book, for given t. This weighting scheme ensures that the exposure concentration of a bank, for bank-specific distress probability, would increase at a higher rate for an increase in distressed probability for a large borrower than for a marginal borrower, as has been argued in the literature [14] and reported in other studies [13] as leverage sensitivity.

The third stage further enriches the distress concentration score with information on the bank's solvency and liquidity condition, such as regulatory capital ratio, non-performing loan ratio, liquidity coverage ratio and multi-factor derived funding/liquidity risk indicator [10]. Further, the literature contains evidence of the propagation of liquidity shocks through interbank markets, which is reflected by the percentage of a bank's funding coming from interbank markets, leading to the inclusion of an interbank contagion term. These bank-level indicators, along with the bank-level exposure-weighted distress concentration in stage two, make up the full feature set which is used in the final integrated classifier [16].

During the fourth stage, the full level of the banks' feature information is employed to train a supervised classifier to predict whether a bank is going to suffer a material adverse event in solvency or liquidity (here defined for illustrative purposes as suffer being an event resulting in a gap in overall liquidity or capital adequacy or in a supervisory intervention within a 12-month horizon). As in recent studies of ensemble methods for bank-failure prediction [17], [18] the main classifier employed in this paper is the XGBoost ensemble, and logistic regression, linear discriminant analysis, a random forest ensemble (RF) and a linear support vector machine (SVM) – for which a maximum-margin formulation was employed – are also compared. To assess the models, accuracy, precision, recall, F1-score and the area under the receiver operating characteristic curve (AUC) are calculated for each model on a held-out test partition after splitting the analysis into 70:30 train–test cohorts, stratified by the outcome to ensure the proportions of distress events in the train and test cohorts were the same.

The hyperparameters of both the tree-based and kernel-based classifiers are obtained through five-fold cross-validation of the training partition before evaluating on the held-out test set, to prevent overfitting in the training set, and thus avoid overoptimistic performance measurements. The hyperparameters tuned for the XGBoost ensemble are the maximal tree depth, shrinkage (learning rate), number of rounds and regularization parameter L1/L2, whilst early stopping is used when validation-set log-loss starts to improve less for a number of rounds. SVM implementation uses RBF kernel, and values of kernel-width and penalty parameter are optimized using grid search. Class imbalance inherent to the distress-prediction problem with the number of material adverse bank-level events being relatively small is handled by using a class-weighted loss function and by employing a stratified cross-validation folds as is typical in the bank-failure-prediction literature [17], [18]. The exposure-weighted distress concentration term is also decomposed by feature importance for the integrated XGBoost model, using gain-based importance scores, which is presented in Section 4, and allows the exposure-weighted distress concentration term contribution to be compared with the contribution from the bank-specific solvency and liquidity indicators [19].

The illustrative set of data we constructed is comprised of pretend information across 1,200 firms, spanning 10 industrial sectors, and 60 simulated banks, allowing each firm to take out loans from 1 or more banks to realize that they often borrow from several banks. The calculations are based on a binary classification of firms as distressed and non-distressed, in which the distressed firms are sampled from the log-normal and beta distributions. The same structure of correlations is applied to the other banks' level variables (capital adequacy, non-performing loan ratio, liquidity coverage ratio, interbank funding ratio) and these are simulated from respective distributions calibrated within viewing range of plausible regulatory targets, as typically drawn from the bank-vulnerability literature [9], [10]. A 2-by-2 binary bank-level outcome variable is then created, using a latent-threshold rule on a weighted sum of the simulated features and some random noise, calibrated to make approximately a twelfth of all observations of bank years adverse (with a broadly comparable low rate of realization of bank distress reported in the empirical bank failure literature, [17], [20]). The lack of access to confidential supervisory loan-level data for this study prohibits the use of these variables to actual data and renders the framework descriptive rather than descriptive-statistical. Since these data are confidential supervisory loan-level data, instead of descriptive-statistical, this study elucidates the framework with these contrived data and sets the values of these financial ratios to match realistic sets of data reported in the cited literature and other economic and bank-level variables to match realistic ranges reported in the cited literature. This design choice enables the methodology, aggregation logic and the comparative model evaluation to be easily made transparent, and helps to make it explicitly clear that there is an important direction of future work with regard to empirical validation on real loan-level supervisory and commercial loan datasets where applicable – as discussed in Section 5.

4. RESULTS AND DISCUSSION

The comparative results of the candidate classifiers described in Section 3, for the constructed illustrative data set are presented here, for the immediate meaning to systemic risk monitoring in early warning lies in the integrated framework: their implications are discussed.

The trade-off between accuracy, precision and recall is mapped in Table 2, together with statistical values for F1 score and AUC of the five candidate models. As presented in Table 2, the proposed integrated XGBoost model outperforms the baseline logistic regression model with an accuracy of 0.91 with an AUC of 0.94 whereas the LR model shows an accuracy of 0.78 with 0.82 AUC. While the discriminant-analysis specification is similar to a classical discriminant analysis [2] it performs slightly better than logistic regression, and is still far behind the ensemble methods. The random forest and support vector machine models fall somewhere between this, as the structural characteristics of financial data has been shown before in these instances, that ensemble tree-based models outperform both classical linear discriminant models and those based on kernels in structured tabular data [17], [18].

Table 2. Comparative Classification Performance of Candidate Models (Illustrative Test-Set Results)

Model	Accuracy	Precision	Recall	F1-score	AUC
Logistic Regression	0.78	0.74	0.71	0.72	0.82
Discriminant Analysis (Altman-type)	0.80	0.77	0.73	0.75	0.84
Support Vector Machine	0.83	0.80	0.77	0.78	0.87
Random Forest	0.85	0.82	0.80	0.81	0.89
XGBoost – Integrated Model (Proposed)	0.91	0.89	0.88	0.88	0.94

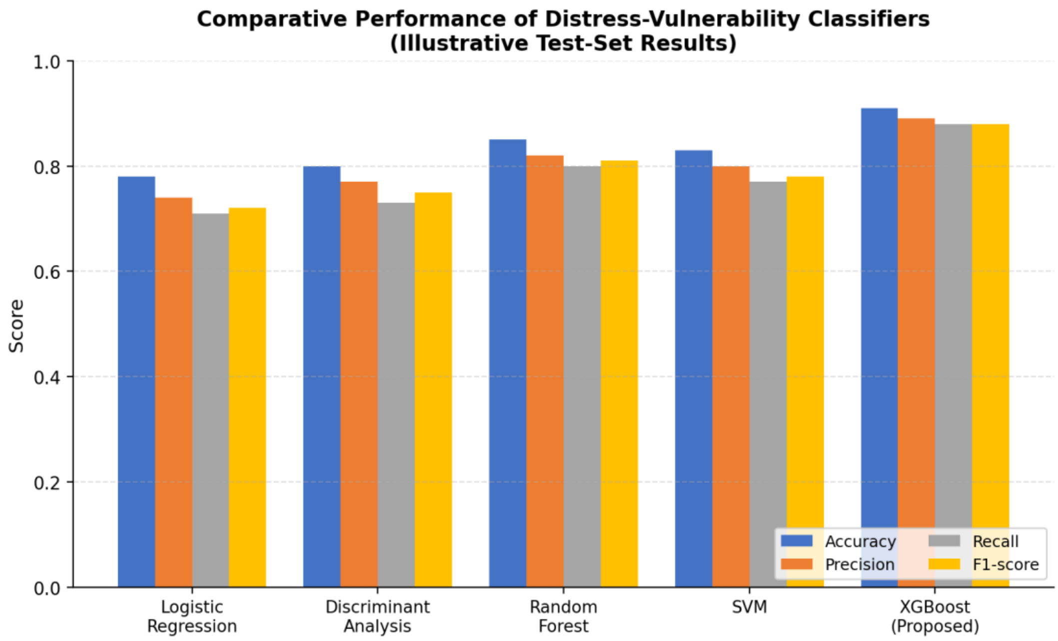

Figure 2. Comparative Performance of Distress-Vulnerability Classifiers Across Four Evaluation Metrics

Bowling down 5 models through the 4 classifiers are visualized as shown in Figure 2. There is significantly greater performance improvement in the integrated model compared to the baseline logistic regression specification for correct identification of banks which subsequently experience an adverse solvency or liquidity event (recall), as seen in Figure 2 an outcome usually of critical importance in the context of supervisory early-warning systems where the cost of a false negative is generally much higher than the cost of a false positive.

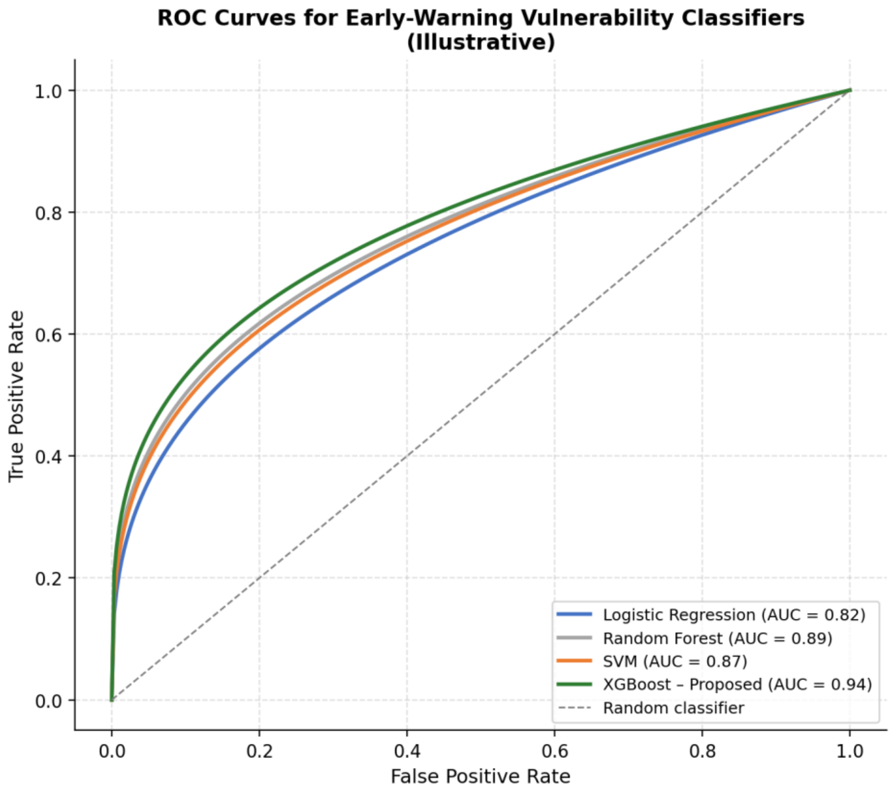

Figure 3. ROC Curves for the Principal Early-Warning Vulnerability Classifiers

Comparative performance of the proposed models is shown in the receiver operating characteristic (ROC) curve in Figure 3. The integrated XGBoost classifier clearly outperforms the other models, and keeps logistic regression, discriminant analysis, random forests and support vector machine higher levels of false positive rates in all of the ROC curve. This is reflected in the peak and optimum area under curve (AUC) obtained as shown in Table 2, which means that the integrated framework has high reliability in discriminating vulnerable banks and non-vulnerable banks for various decision thresholds. This flexibility can be highly beneficial for supervisory authorities, which can adapt classification limits based on the macro-financial situation. In times of strong credit growth or anxious investors, regulators may choose to call back more banks, potential troubled banks, even with the drawbacks of false alarms.

Apart from its high predictive accuracy, the seamless 'package' provides many crucial hands-on benefits over traditional single-layer solutions. The added DWM provides a breakdown of bank vulnerability, incorporating a concentration risk component because of the exposure to a small number of borrowers who are significantly distressed versus a diffuse risk component because borrowers are generally mildly distressed but in many numbers. Traditional ratios do not do this at the level of the banks in particular. In addition, it allows for flexible application with all types of information provided by borrowers. Market-based types of distance-to-default measures can be applied to listed firms and accounting-based financial ratios applied to unlisted firms, and this way both information sources can be integrated into a single supervisory framework without having to make any changes to the structures.

The results are also in line with the general pattern of the corporate financial distress and banking sector fragility literature. Leverage and liquidity variables' importance in the firm-level distress prediction is consistent with most of the previous literature findings, which reported the role of funding and liquidity risk in financial instability. Likewise, the relevance of market-based indicators reinforces past studies showing that often the market offers important early signals of the deterioration of the financial environment. The exposure concentration and interbank funding variables at the banking level corroborate past research on how ownership relationships and an interconnected lending structure contribute to amplifying contagion risk. The outcomes are consistent with the general hypothesis of this study that the corporate distress - bank vulnerability continuum is not separable but can be considered jointly to assess financial risk transmission.

This is further corroborated by the feature importance analysis from the XGBoost model. The distress concentration indicator, which is also the most recent of all of the explanatory variables, makes the largest contribution to the predictive power, followed by the non-performing loan ratio, the liquidity coverage ratio and the share of interbank funding. The capital adequacy, has a negative non-effectary on the simulated data and, although statistically significant, the marginal contribution is rather smaller. The conclusion is that fall in borrower quality is a more influential real-time determinant of bank vulnerability, independent of capital buffers. Further, in the decline in asset quality vs capital adequacy, nonlinear interactions are naturally captured by the tree-based ensemble model, while linear models (e.g., logistic regression) will have reduced capability of modelling such interactions. This is in line with structural credit risk theory that highlights that a bank's own solvency will be reliant on the credit quality and asset values of the underlying borrowers.

In a regulatory context, the results suggest that purely indicator-based supervision (based on levels of, for instance, non-performing loans) can be misleading when it comes to assessing vulnerabilities in banking systems that have a small number of large borrowers, including those that are financially vulnerable. The use of forward-looking firm-level distress signals in early-warning monitoring systems can, therefore, enhance the timeliness of the systems by better detecting firm distress signals before such distress signals appear in standard early-warning asset-quality measurements. The ability is useful especially in macroprudential supervision to address sector-specific shocks that can quickly spread through concentrated loan portfolios and through interlinkages between banks.

Though these results were encouraging, it should be recognized there were a number of limitations. Firstly, the empirical analysis is on a simulated dataset and not on confidential supervisory / loan-level data, and hence a proof of concept rather than real-world predictive performance. Second, the period of the prediction horizon (namely 12 months) is fixed and other prediction horizons can produce different outcomes on the comparative effectiveness of the modelling methods. Lastly, qualitative jurisdiction-specific aspects of insolvency have been taken into account, but further in-depth legal and institutional variables should take account of local differences in bankruptcy regimes (including creditor protection) across countries. Extensions to the proposed framework that include macroeconomic variables, network structures and multi-period survival modelling, and validation using real supervisory datasets, could complement the framework and improve its use for financial stability monitoring and systemic risk assessment.

5. CONCLUSION

This paper suggests an integrated four-stage risk assessment model that connects the financial distress prediction model of the firms to the risk assessment models of banks and systems. The framework features an interpretable systemic risk signal, based on firm distress scoring, exposure-weighted bank aggregation, bank-specific solvency and liquidity indicators, and an ensemble of machine-learning classifiers. An illustrative data set showed that recall exceeded that of classical classifiers (logistic regression, discriminant analysis, random forest, and support vector machines), eventually making the gradient-boosting perform better than the other models, hence its viability for the early-warning applications considered, where the identification of vulnerable institutions is a key factor. One of the major achievements of this framework is that it is transparent, allowing supervisors to backtrack to the individual firm or portfolio or liquidity concerns, not only use the bank-level: financial ratios only. However, these results have been created using an artificial data set and should be applied and tested in other jurisdictions and with actual supervisory and loan-level data. A textural disclosures approach, a network-based approach, a cross-border-based approach, a survival-based approach and a macroprudential stress-testing approach should be added to future research to enhance predictive capability. The framework is also extensible to be implemented step-by-step and, for regulators or banks, allowing them to validate each module separately before deploying the full system. This gradual approach also helps make the use of the model more feasible in practice, and provides good support for model validation based on relatively small amounts of supervisory information, as well as for the integration of corporate financial distress analysis and financial stability monitoring of the banking sector.

Acknowledgments

The authors have no specific acknowledgments to make for this research.

Funding Information

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Author Contributions Statement

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Sanjana Amarjeet	✓	✓	✓	✓		✓		✓	✓	✓	✓		✓	✓

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

Conflict of Interest Statement

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Informed Consent

All participants were informed about the purpose of the study and their voluntary consent was obtained prior to data collection.

Ethical Approval

Not applicable.

Data Availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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How to Cite: Sanjana Amarjeet (2026). Corporate financial distress and banking sector vulnerability: an integrated risk assessment approach. Journal of Corporate Finance Management and Banking System (JCFMBS), 6(1), 102-113. https://doi.org/10.55529/jcfmbs.61.102.113

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